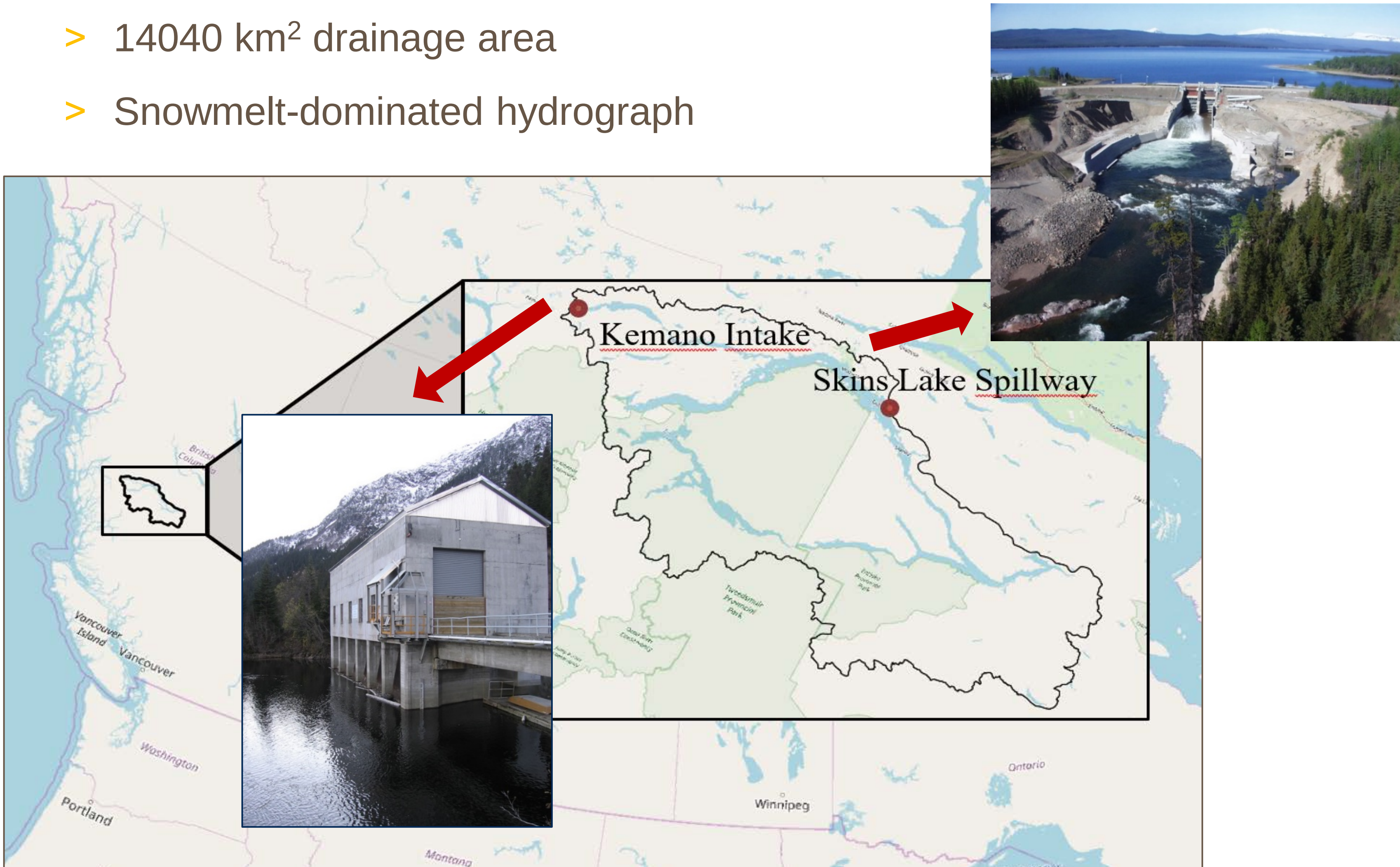
Assessing the impacts of integrating snowpack error distribution in the management of a hydropower reservoir using Bayesian Stochastic Dynamic Programming (BSDP)

Richard Arsenault*, Pascal Côté and Marco Latraverse

École de technologie supérieure
Department of construction engineering
Montréal (QC), Canada, H3C1K3
+1-514-396-8743
Richard.arsenault@etsmtl.ca

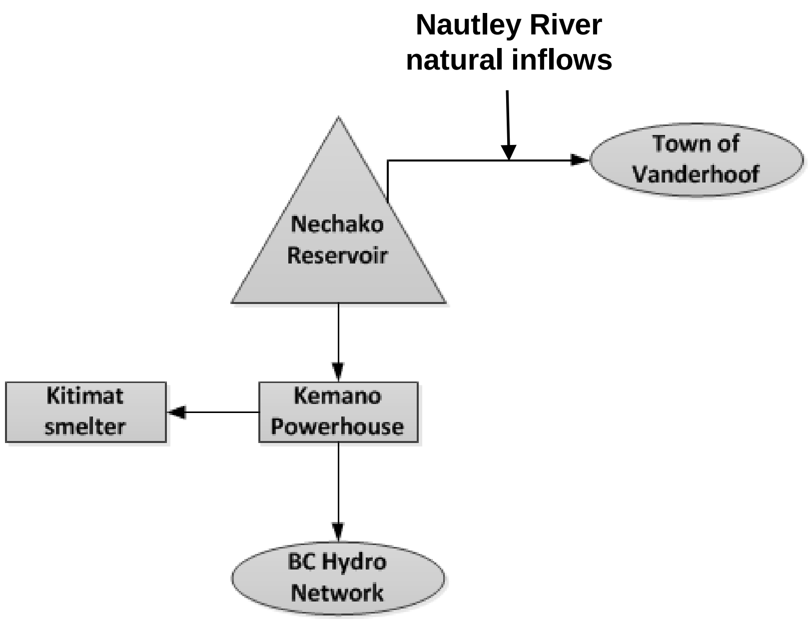
Hydropower System

- **Kemano Hydropower System in B.C., Canada**
- 14040 km^2 drainage area
- Snowmelt-dominated hydrograph



Hydropower System

- **Rio Tinto Kemano System in B.C. Canada**
- Water release decisions aided by an SDP implementation
- A hydrological variable representing the water content of the catchment, including Snow-Water Equivalent (SWE), is used as a predictive variable of future inflows in SDP



Challenges

- Impact of snowmelt is paramount in the management of the hydropower system.
- High uncertainty around SWE measurements (4 snow pillows, 7 core-sampling sites)
- Spatial variability of SWE is very high (2000mm precip. in the mountains, 400mm in the plains)

Objective:

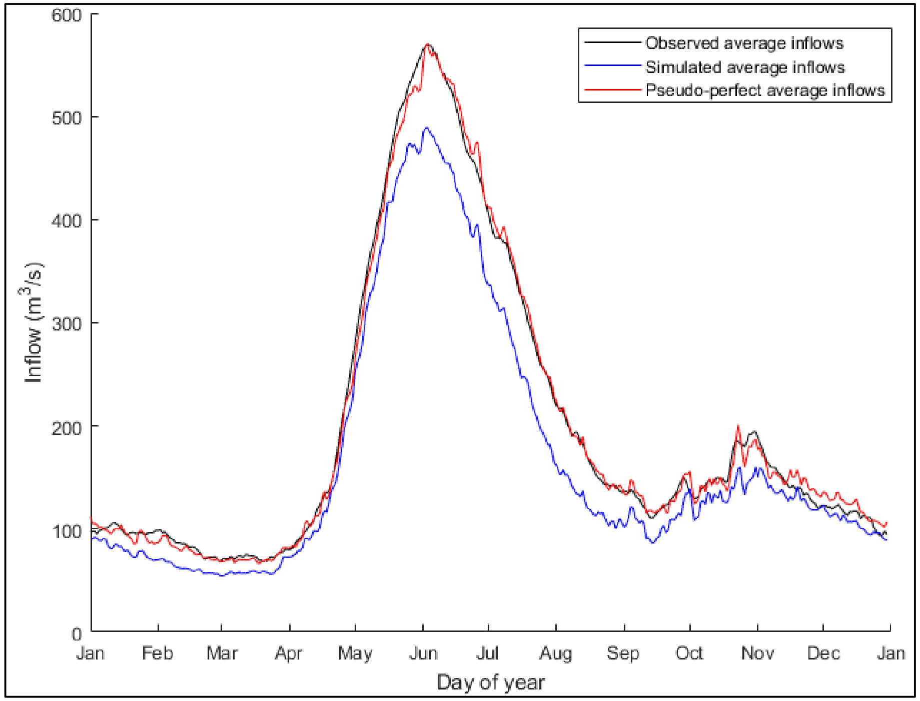
- Evaluate uncertainty around hydrologic variables (including SWE) and use this information to improve the water release policy in a Stochastic Dynamic Programming Framework

Methods

> **Distributed hydrological model (CEQUEAU) – 2 simulations**

(1) Ordinary simulation, using actual measured Precip. and Temp.

(2) « Pseudo-Perfect » simulation, using fitted Precip. and Temp. time-series to perfectly reproduce inflows;



> Each simulation also returns state variables, such as SWE

> We can estimate the bias and uncertainty in the hydrologic variable by comparing both simulations

Methods

> Current Policy given by SDP:

$$\pi_t(s_t, h_t) = \operatorname*{argmax}_{u_t} \left\{ \mathop{\mathrm{E}}_{q_t|h_t} \left[B_t(s_t, u_t, q_t) + \mathop{\mathrm{E}}_{h_{t+1}|h_t} [F_{t+1}(s_{t+1}, h_{t+1})] \right] \right\}$$

> With the water value function computed as:

$$F_t(s_t, h_t) = \max_{u_t} \left\{ \mathop{\mathrm{E}}_{q_t|h_t} \left[B_t(s_t, u_t, q_t) + \mathop{\mathrm{E}}_{h_{t+1}|h_t} [F_{t+1}(s_{t+1}, h_{t+1})] \right] \right\}$$

> However, operationally we do not have perfect values.

> In operations, we add the error distribution of h_t in the SDP policy:

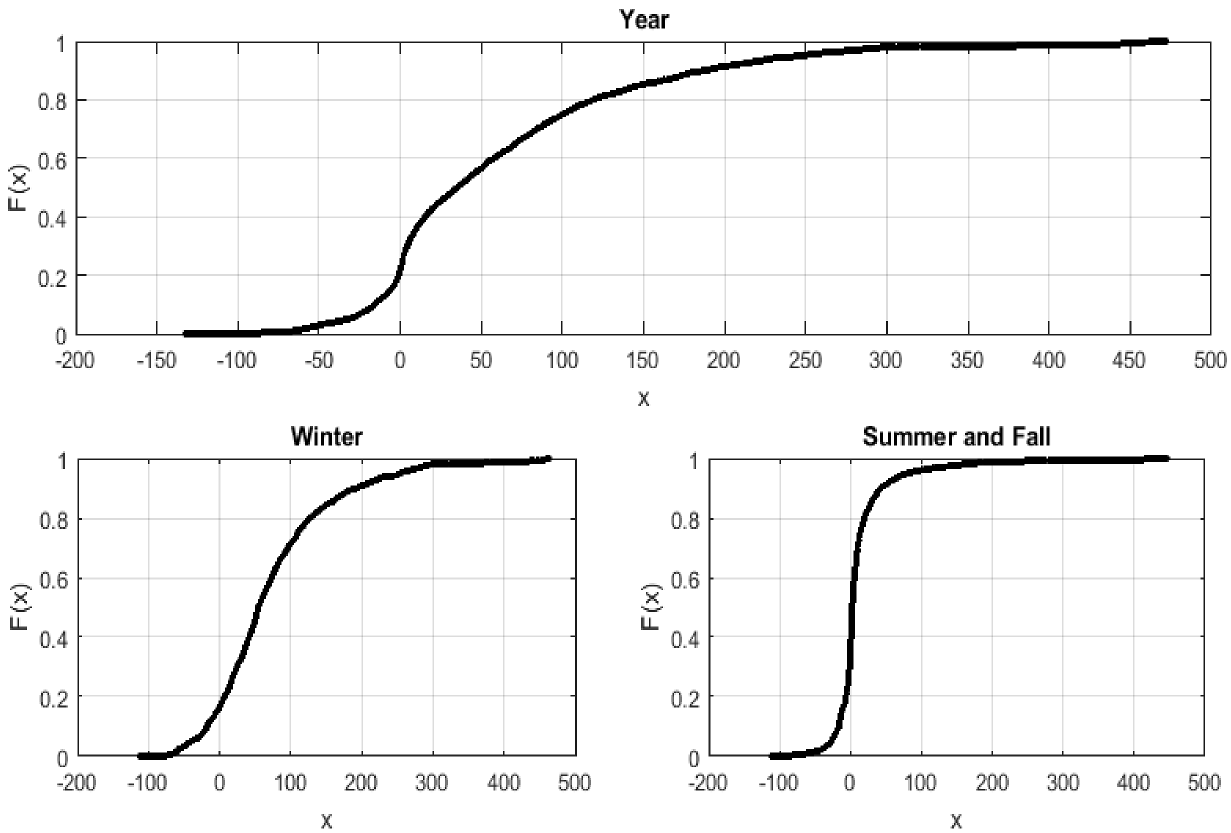
$$\pi_t(s_t, h_t) = \operatorname*{argmax}_{u_t} \left\{ \mathop{\mathrm{E}}_{h_t|\hat{h}_t} \left[\mathop{\mathrm{E}}_{q_t|h_t} \left[B_t(s_t, u_t, q_t) + \mathop{\mathrm{E}}_{h_{t+1}|h_t} [F_{t+1}(s_{t+1}, h_{t+1})] \right] \right] \right\}$$

> Where the error distribution of h_t is computed and updated at the end of each season when the pseudo-perfect weather timeseries can be generated.

Results

> **Error distribution relative to the season**

The hydrological variable also includes soil humidity, which is negligible in winter but becomes important in summer. Units in mm of water.

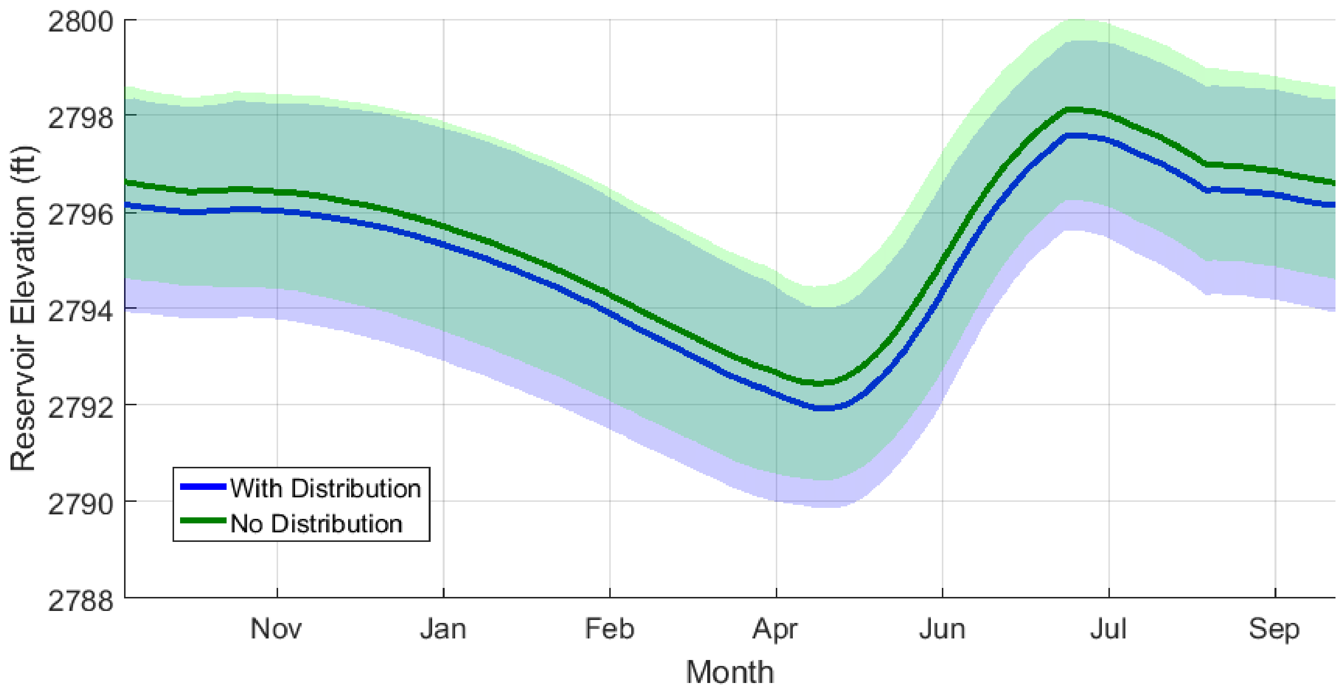


Simulation Results

RioTinto

> Impact on water management

Hydrological Variable	Avg. Annual Export and Aluminum	Daily Probability of Shortage	Daily Probability of Flooding
Pseudo-perfect Corrected	106.1	6,5%	0,1%
Real, No Distribution	100.0	6,0%	0,5%
Real, With Distribution	103.1	6,0%	0,2%



Analysis and conclusions

- BSDP naturally corrects the Hydrologic Variable bias
- Lower reservoir level on average: probably due to correction of precipitation undercatch
- More efficient generation due to better uncertainty representation
- Less flooding, more energy for same shortage risk.

- Bayesian SDP has shown to be a promising water resources management tool
- Pseudo-perfect simulations can be very valuable to estimate the error distributions (rather than embarking on measurement field trips)

Assessing the impacts of integrating snowpack error distribution in the management of a hydropower reservoir using Bayesian Stochastic Dynamic Programming (BSDP)

Richard Arsenault*, Pascal Côté and Marco Latraverse

École de technologie supérieure
Department of construction engineering
Montréal (QC), Canada, H3C1K3
+1-514-396-8743
Richard.arsenault@etsmtl.ca